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Opto-Electronic Neural Networks Based on Few-Mode Fiber

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Abstract—In this work, for the first time to our knowledge, the spatial degrees of freedom are introduced to opto-electronic neural networks, and the few-mode fiber based multiplexing is numerically simulated to realize parallel synapses.

Keywords: opto-electronic neural networks; few-mode fiber; spatial degrees of freedom; machine learning;

I. INTRODUCTION

In recent years, electronic neural networks (ENNs) have been extensively used in many tasks such as optical performance monitoring, signal processing and image recognition [1-3]. However, due to the limitations of computational speed and energy efficiencies in the electronic hardware, ENNs cannot easily meet the requirements of high-speed computing applications, e.g. autonomous driving, medical diagnostics and robot control [4-6]. To overcome the limitation of ENNs, new approaches to realize weighted synapses that connect neurons and nodes in neural networks (NNs) need to be developed. Instead of using electrons as carriers for signal transmitting and processing, optical neural networks which employ photons as information carriers can process the signals at the speed of light and do not require additional powers to transmit information between memory modules and computing units [7]. Considering the complexity of neural networks, it is necessary to introduce new spatial degrees of freedom to emulate neurons and to implement parallel synapses. Few-mode fibers (FMFs) have attracted significant attentions due to their great potentials to solve the capacity crunches through the mode-division multiplexing (MDM) technique [8]. Meanwhile, the parallel computing capability of FMFs shows a wide prospect in their application in optical neural networks.

In this paper, we propose a new structure of opto-electronic neural networks based on the FMF to implement the feedforward fully-connected NNs. The employed FMF is a 5-mode fiber with a uniform differential group delay (DGD). To further reduce the length of the fiber, an FMF with a larger number of guided modes can be applied. The dispersion effect of the fiber plays a dominant role in the pulse broadening, which allows a multi-dimensional modulation on the pulse. The proposed opto-electronic

neural network scheme is composed of an optical computing module and an electrical computing module. The forward linear calculations of the NN, e.g. the product and the weighted sum of input signals, are performed using the optical neural network, while the nonlinear and the back-propagation operations of the NN are still carried out by electronic devices.

II. STRUCTURE AND PRINCIPLE OF THE OPTO-ELECTRONIC NEURAL NETWORKS

As the core part of the opto-electronic NN, neurons play a key role in the calculation of the weighted sum of input data. In our system, neurons are emulated using optical pulses, and the number of pulses is determined in accordance with the number of neurons (excluding virtual neurons) in the next layer. The pulses are broadened by the fiber dispersion, and the weight matrix and the input vector are modulated onto the FMF by intensity modulators. The FMF with the uniform DGD can provide the spatial degrees of freedom, leading to a significant reduction of the broadening of pulses in each mode, compared to the use of the single-mode fiber (SMF).

The structure of the proposed opto-electronic NN is illustrated in Fig. 1. Optical pulses are generated from a pulse laser. The DGD of the FMF will stagger the pulse sequences in different modes, producing a time-domain multiplexer, and the number of channels in such multiplexer is determined by the number of FMF modes. After passing through the FMF, the pulses are broadened and spaced with a uniform time interval. Then the pulses are modulated by the weight matrix (W) and the input vector (X) (from the previous loop) through the intensity modulator 1 and the intensity modulator 2. Since only positive input coefficients can be modulated via the intensity modulator, the original weight matrix will be divided into two matrices, w_+ and w_- , to perform calculations, separately. The w_+ matrix inherits positive coefficients from the original weight matrix, and fills all negative components with zero values. The w_- matrix takes the absolute value of negative components in the original weight matrix, and fills positive coefficients with zero values. The network considers the bias b as a virtual weight, which will be multiplied by a virtual neuron with a

value of 1. The narrow-band PD is used to receive pulses and works as a pulse energy accumulator. Note that the mode

multiplexer and demultiplexer are not shown in Fig. 1, which

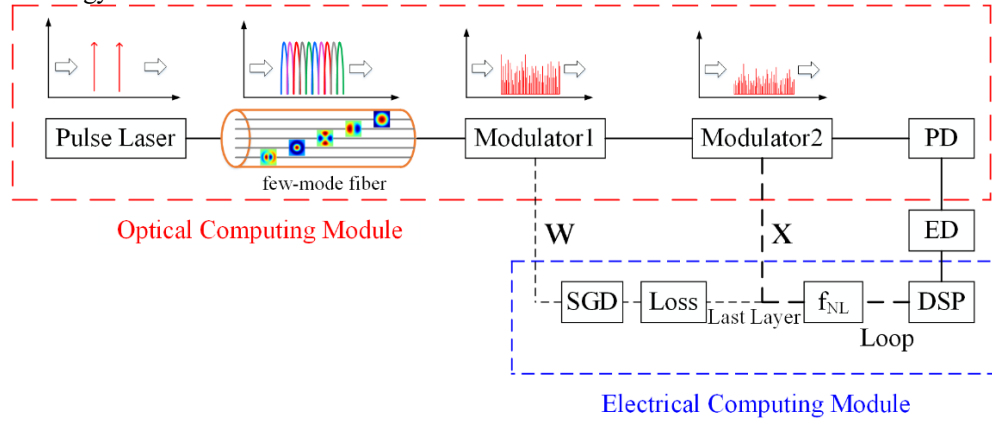


Fig. 1 Structure of the opto-electronic neural network. ED: electronic device.

can be realized by the device such as the multi-plane light converter (MPLC).

The linear calculation of each neuron is given by

$$h_o = \sum_1^n w_{+k} x_k - \sum_1^n w_{-k} x_k \quad (1)$$

where x_k is the input signal, w_{+k} and w_{-k} are the positive and the negative weight matrices, respectively.

After the linear calculation in the optical computing module, the signal is fed into the electronic calculation module. The signal is then processed by DSP and the result for the nonlinear activation function is

$$h = f_{NL}(h_o) \quad (2)$$

where f_{NL} is the nonlinear activation function.

In the neural network, the output of the first layer is used as the input of the second layer. In our system, the loop connects adjacent network layers, where the output of the previous loop is applied as the input vector of the next layer. The calculation in subsequent layers will be implemented accordingly. The loss will be calculated and the gradient descent will be completed, after the nonlinear calculation in the last layer, to facilitate the next iteration of training.

III. OPTO-ELECTRONIC NEURAL NETWORKS FOR HANDWRITTEN DIGIT RECOGNITION

To verify the performance of the opto-electronic NN, numerical simulations of the handwritten digit recognition based on Modified National Institute of Standards and Technology (MNIST) test set is evaluated for the ENN at first [9]. The preprocessing and the training process of the ENN is shown in Fig. 2. The NN applied here is a fully-connected network with three layers, including an input layer, a hidden layer and an output layer. All activation functions are sigmoid functions with non-negative outputs. The pictures in the training and test set are all resampled from (28, 28) to (20, 20). After the flattening of pictures, the number of neurons (including a virtual neuron) at the input layer is 401. The number of applied neurons (including a virtual neuron) in the hidden layer is 21. Since the considered handwritten digit recognition is a 10-instance

classification task, the number of output neurons is 10. The most commonly used mean-square-error (MSE) is selected as the loss function. The classification accuracy on the training set is over 95%. To verify the performance of the ENN over the test set, all 10000 sets of data were fed into the ENN after the completion of the training with 60000 sets of training data. In all 10000 sets of data, there are 9514 sets providing predictions identical to true values. This indicates that the accuracy of the ENN in the test set is 95.14%.

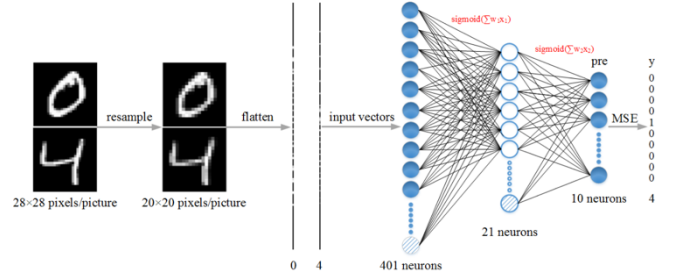


Fig. 2 The preprocessing and training process of the ENN.

The performance of the opto-electronic NN over the handwritten digit recognition data set is also numerically simulated using the VPItransmissionMaker software. The structure of the opto-electronic NN used for the handwritten digit recognition is shown in Fig. 3. The repetition frequency and the duration of the pulse (full width at half maximum, FWHM) are 100 MHz and 5 ps, respectively. An FMF is used to broaden the pulse in time domain. The FMF is a 5-mode fiber with a dispersion coefficient of 20 ps/km/nm. Since the time interval between two adjacent original pulses is 10 ns, after the propagation along the FMF, the pulses in each mode are expected to be broadened to 2ns (full width). When the length of the fiber is 50 km, the FWHM of the pulse after the broadening will be around 0.71 ns and the full width will be about 2 ns. The DGDs of the 5-mode fiber are chosen as -0.04 ps/m, -0.08 ps/m, -0.12 ps/m and -0.16 ps/m, respectively. The broadened pulses will then be fed into two arbitrary waveform generators (AWGs) and two 40-GHz intensity modulators. The weight matrix is projected from the electronic devices to AWG1 while the input vectors are

mapped from the compressed picture pixels to AWG2. The bandwidth of the PD is set to be 200 MHz so that the PD can

be used as an accumulation device.

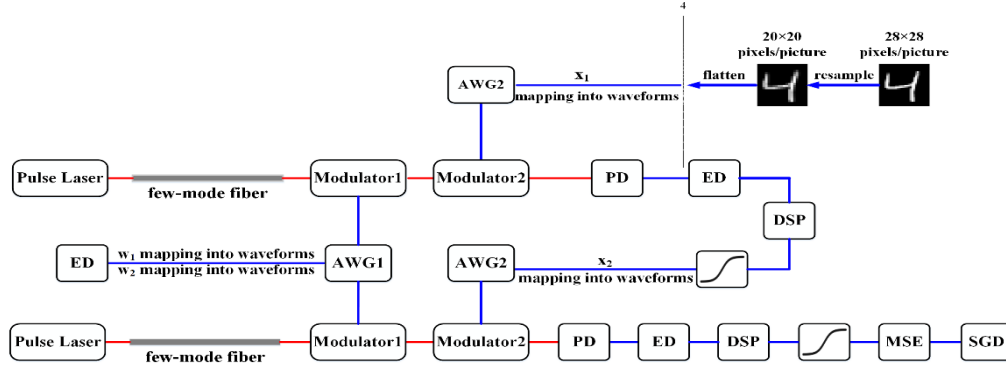


Fig.3. Structure of the opto-electronic neural network used for the handwritten digit recognition.

After the linear calculation in the optical computing module, a series of ENN computations will be conducted by electronic devices. Figure 4 depicts the accuracy curve of the training process in the opto-electronic NN. The loss value of the network decreases fast in the first ten epochs and then gradually converges. It can be seen in Fig. 4, the final classification accuracy on the training set is over 92%.

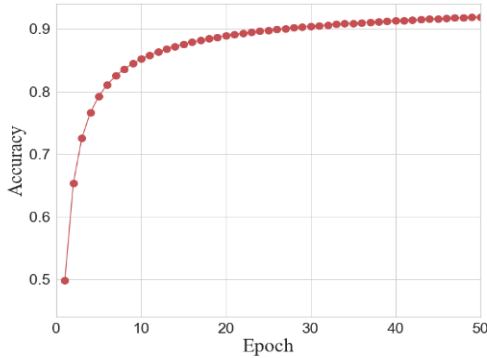


Fig. 4 Accuracy versus epoch during the training process.

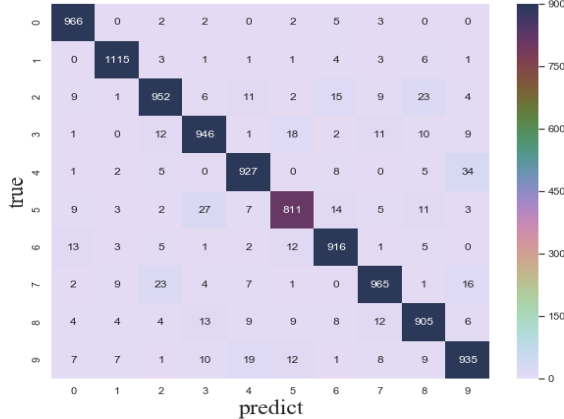


Fig. 5. The heatmap of the confusion matrix for the analysis of the accuracy over the test set.

Figure 5 shows the confusion matrix of the predicted results and the true results. The classification accuracy of the opto-electronic NN over the test set is evaluated as 94.38%. This indicates that the designed opto-electronic NN can provide a good performance for classification

computation and the achieved accuracy is similar to the performance of the purely electronic NNs.

IV. CONCLUSION

In this work, a new structure of the opto-electronic neural network is proposed and implemented based on the use of FMF. Numerical simulations of a 3-layer ENN for handwritten digit recognition is investigated as the benchmark, with an accuracy of 95.14% achieved over the test set. The optical computing module, which uses photons as the information carrier, can significantly improve the computing speed of the NN and the power efficiency, compared to the use of electronic devices. In the optical computing scheme, the weights are all modulated with Gaussian pulses. In numerical simulations, the influence of the Gaussian pulses on the weight is taken into consideration, and the classification task over the handwritten digit recognition data set using a 3-layer opto-electronic neural network is performed, with an accuracy of 94.38% achieved. This proposed multiplexing approach provides a new solution with great potential in the applications of high-speed NN computing.

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